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Original Article

Can implicit cognition predict the behavior of professional energy investors? An explorative application of the Implicit Association Test (IAT)

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ABSTRACT

This article reports on the results of two studies involving seventy-seven professional investment managers in Switzerland. We designed an Implicit Association Test (IAT) to investigate whether unconscious attitudes toward renewable versus non-renewable energy sources influence investment behavior. In Study 1, we find that there is indeed a correlation between implicit associations and our dependent variable, net investment in solar energy. In Study 2, we replicate the results from Study 1 and also show that implicit associations are more strongly correlated to investment behavior than explicit associations, suggesting that application of the IAT may add value to the analysis of energy investor behavior. As an example of investigating factors influencing decision-making "in the wild", our study is subject to a number of limitations that can be used as starting points for further research in this area of high societal relevance.

1. Introduction

"Investing in solar energy is fraught with policy risk", "In the solar market, we simply don't see the returns we are looking for", "Generating solar energy in Germany makes as much sense as growing pineapples in Alaska". When assessing the risk-return profile of investing in solar energy compared to their core business of non-renewable energies, many energy industry professionals until recently expressed an intuition that suggests they do not associate this newly emerging technology with what they would consider a good investment. A particular case in point are the two oil industry managers who made the first two statements above to one of the co-authors in 2009, when talking about their company's decision to divest from a solar technology company, only to enthusiastically go on and talk about their latest investment in a Siberian oil field – which they implicitly seemed to associate with lower levels of policy risk.

As these examples show, there may be more to the assessment of energy investment opportunities – especially in the high uncertainty environment of investing in new innovative technologies – than the sophisticated analytical processes usually described in corporate finance textbooks. In fact, more subtle, conscious or unconscious associations of certain investment targets like solar energy or fossil fuels to attributes like "risk" and "return", or more generally "positive" and "negative", seem to be also present in decision-makers' minds. Investigating such associations and uncovering their influence on actual investor behavior could strengthen existing models of decision-making, potentially contributing to solving prevalent empirical puzzles, such as why despite mounting evidence of global climate change (IPCC, 2014), investors appear to be locked in to existing investment patterns (Unruh, 2000).

An obvious challenge, however, is that by their very nature, implicit associations are hard to measure. Common methodological approaches in management research, such as relying on expert interviews or document analysis, will therefore fall short of providing an accurate account of the unconscious elements that may be powerful elements of decision-making (Greenwald & Banaji, 1995; Nisbett & Wilson, 1977; Uhlmann et al., 2012). Recent advances in psychology have offered new insights and methodological tools, allowing to open the black box and get a "window to the mind" of decision-makers. A particular example is the Implicit Association

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Test (IAT) developed by Greenwald, McGhee, and Schwartz (1998) and applied in a wide range of decision areas (for an overview, see Bargh, 2007; Fazio & Olson, 2003; Greenwald, Poehlman, Uhlmann, & Banaji, 2009; Hofmann, Gschwendner, Nosek, & Schmitt, 2005; Uhlmann et al., 2012). Most of the IAT applications so far have been conducted with student or consumer samples, leaving the question unanswered whether implicit associations also play a role in the context of experienced professional decision-makers, and if so, how this links to the choices they make. This paper describes, to the best of our knowledge, the first application of the IAT to a sample of professional investment managers in the energy domain. In two studies with a total of seventy-seven energy investors, we measure their implicit associations toward solar energy and gas, and explore their influence on investment behavior.

The context of our research is a high-uncertainty investment context, the Swiss energy transition. After the Fukushima nuclear accident in 2011, the Swiss government decided to phase out nuclear power, currently accounting for 40% of the country's electricity generation, while sticking to its greenhouse gas emission reduction targets (www.energiestrategie2050.ch). As a consequence of this political decision and the cost reductions that occurred in solar energy worldwide, many observers see investment in solar energy as a huge market opportunity (Aanesen, Heck, & Pinner, 2012; Bazilian et al., 2013; Della Croce, Kaminker, & Stewart, 2011). However, accurately predicting future cash flows from investing in solar or other energy technologies is a challenging task, given dynamic technology development, volatility in the price of fossil fuels, and a changing policy landscape. In this context, professional energy investors, including both electric utilities and financial investors such as banks and pension funds, have been slow to pick up on the solar opportunity in Switzerland (Windisch, Friedrich, Wanner, & Wüstenhagen, 2011). In contrast, homeowners and other non-professional energy investors were much faster to react, to the extent that – similar to what has been observed in other countries (Helms, Salm, & Wüstenhagen, 2015) – 80% of all new photovoltaic power generation capacity is now owned by private investors or commercial roof owners (Chassot, 2012). Interestingly, many Swiss homeowners report to rely on their intuition rather than sophisticated forms of financial analysis when making such building-related energy investments (Ebers & Wüstenhagen, 2015).

While this paper does not attempt to take sides in the raging debate whether – or rather: under which environmental conditions – intuitive or analytic processes lead to better decisions (Samuels, Stich, & Bishop, 2002; Gigerenzer, 2007; Kahneman, 2011), our objective is to explore professional investors' implicit associations to renewable versus non-renewable energy sources, and to understand whether those are reflected in their investment behavior. Additionally, as is common practice in many IAT studies (Greenwald et al., 2009) and in order to ensure validity of our findings, we distinguish implicit from explicit associations, and test if the impact of implicit cognition on decision-making prevails if we control for explicit associations to renewable versus non-renewable energy sources.

Our research questions, therefore, are:

(1) What is the impact of implicit cognition on decision-making of professional energy investors?
(2) In a high uncertainty context, is implicit cognition more closely linked to actual behavior than explicit cognition?

The rest of the paper proceeds as follows. Sections 2 and 3 present the two empirical studies (including methods, results and discussion), Section 4 contains a general discussion of our findings, and concludes the paper with practical implications, limitations and suggestions for further research.

2. Study 1

2.1. Method[1]

2.1.1. Implicit Association Test (IAT)

An IAT tests how strongly the participant implicitly associates a concept (e.g. an energy source such as *solar energy*) with an attribute (e.g. *good* or *bad*, *return* or *risk*). The association strength is measured in relative comparison with association of a second concept (e.g. *gas*) to the same attribute, which makes this method particularly applicable to decision contexts where choices are often made between contrasting categories (e.g. the decision to invest in either solar energy or gas). The test operates by presenting pairs of target categories and attributes in two opposing constellations, to find out whether one is more compatible with implicit associations in the respondent's mind than the other, and then asking respondents to assign stimulus words appearing in the middle of the screen to either target categories or attributes on the left or right side of a screen, and measuring reaction times for this task. As Nosek, Banaji, and Greenwald (2002) explain, the crucial assumption of the IAT is that it ought to be easier to pair concepts that belong together in a participant's mind. For example, most respondents would spontaneously rather associate the concept *flower* with the attribute *pleasant* than the concept *flower* with the attribute *unpleasant*. "The extent to which it is easier to pair *flower* + *pleasant* (in the presence of a contrasting pair, e.g., *insect* with *unpleasant*) compared with the opposite pairings (e.g. *flower* + *unpleasant* and *insect* + *pleasant*), the stronger is the assumed positive implicit evaluation of flowers relative to insects." (Nosek et al., 2002, p. 45 f.) In this example, ease or strength of association is measured by the speed to respond under a compatible constellation (e.g., *flower* + *pleasant*) compared with an incompatible constellation (e.g., *flower* + *unpleasant*).

We applied the IAT to measure implicit cognition on renewable vs. fossil energy. Instead of *flower* and *insect*, our target categories were *Photovoltaics* and *Gas* in Study 1. Instead of the attributes *pleasant* and *unpleasant*, we used *Risk* and *Return*. This led to the two test constellations illustrated in Fig. 1, where in one case *Photovoltaics* was paired with *Return* on the left and *Gas* with *Risk* on the right side of the screen (task 1), while in the other case *Gas* was paired with *Return* and *Photovoltaics* with *Risk* (task 2). In both tasks illustrated in Fig. 1, stimulus words like for example *Renewable Energies* appeared in the middle of the screen. As the participant learned in the first part of the test and could also recognize by the font color, this stimulus belongs to the target category *Photovoltaics*. Therefore, in the first task, where *Photovoltaics* was on the left hand side of the screen grouped with *Return*, participants had to assign the stimulus to the left hand side by pressing the "e"-key on the keyboard. In the second task, the target word *Photovoltaics* appears on the right hand side of the screen together with *Risk*. The correct answer here was to assign the stimulus word *Renewable Energies* to the right by pressing the "i"-key. A participant with a stronger association of *Photovoltaics* to *Return* should be faster in task 1 than in task 2, because for him, the combination of target categories and attributes in task 1 represents the compatible constellation, whereas the opposite combination in task 2 represents the incompatible constellation, which requires additional processing time. The IAT measures differences in reaction times between the tasks (in milliseconds), and calculates for each respondent a *d*-score, which indicates relative speed of reaction under the two contrasting constellations – and is hence a measure

[1] The easiest way to understand how an IAT works is to participate in one; demo tests are available online on the homepage of Project Implicit, which was founded by Greenwald, Banaji and Nosek, who developed the IAT. https://implicit.harvard.edu/implicit/takeatest.html

Fig. 1. Illustration of two IAT tasks. In both tasks, the stimulus word *Renewable Energies* had to be assigned to the target category *Photovoltaics* – so in the task on the first screenshot, participants assigned the stimulus word *Renewable Energies* to the left hand side of the screen by pressing the "e"-key. In the task on the second screenshot, participants assigned the stimulus word *Renewable Energies* to the right hand side of the screen by pressing the "i"-key.

Table 1
Target categories, attributes and stimuli of the IAT (Study 1).

Target categories	Stimuli
Photovoltaics	Solar cells, small-scale, solar energy, renewable energies
Gas	Natural gas, large-scale, gas fired, fossil
Attributes	
Return	Growth, profit, cash flow, yield
Risk	Insecure, policy risk, downside risk, hazard

for relative strength of association between target categories and attributes.

In total, each participant had to complete 180 such assignments as the two illustrated in the figure above. If the first answer was false, the participant received an error message and had to repeat the assignment. Throughout the test, participants had to accomplish the assignments *as fast as they could*. Before starting the test, a table with all stimulus words is presented to the participants so that they understand what target category or attribute each stimulus belongs to (see Table 1).

It is crucial that test participants know clearly which target category or attribute a stimulus word belongs to. In order to use the appropriate wording to mirror investment decision-makers' context when designing the IAT, we used transcripts from 20 expert interviews with investment decision-makers conducted in an earlier part of our overall research project (Chassot, Wüstenhagen, Beglinger, & Bärtsch, 2013). The interviews included decision-makers from electric utility companies ($n = 5$), pension funds ($n = 6$), banks ($n = 6$), and insurance companies ($n = 3$).

We calculated the IAT-score (or d-score) using the scoring algorithm by Greenwald, Nosek, and Banaji (2003). A first step was data cleaning (exclusion of participants with reaction times greater than 10,000 ms and for whom more than 10% of tasks have latency less than 300 ms). The IAT-score is the normalized difference of reaction times across the two constellations of Fig. 1 – a real number ranging from −2 to 2.[2] Cohen (1977) suggests the following cut-off values for association strength: scores between |0.15| and |0.35| imply a slight difference between the compatible and incompatible constellations of the assignment, |0.35|–|0.65| moderate, and values above |0.65| a strong difference. The final IAT-score is lower than |0.15| if a participant is indifferent between the two target categories (here: energy sources). We programmed the test such that a positive IAT-score indicates more positive associations to solar energy (and negative associations to gas), and a negative IAT-score indicates more positive associations to gas (and negative associations to solar energy). The final IAT-score is a *relative* measure of the implicit preference for one energy source over the other, so in this case a preference for solar energy over gas.

2.1.2. Dependent variable net solar energy investments

In survey questions following the IAT, we collected detailed information about participants' investments in different energy sources. The 20 expert interviews at the beginning of our research project revealed that most investment decision-makers could not precisely quantify specific investment amounts per energy source. However, interviewees knew rather precisely which asset classes (e.g. shares of a publicly listed renewable energy company, direct financing of a renewable energy project, etc.) they used to invest in different energy sources, and that higher investment exposure in a specific domain implied that investors used several asset classes to invest in that domain. The grid item to survey investments in Study 1 consisted of seven asset classes: private equity, publicly listed equity, real estate, bonds, project finance, commodities/other real assets, and "other". We asked respondents to indicate all of the asset classes through which they invested in solar and gas respectively, and used that information to construct the dependent variable net solar energy investments as the sum of asset classes a participant uses to invest in solar energy, *minus* the sum of asset classes a participant uses to invest in gas. A positive number on the dependent variable indicates a relatively stronger investment exposure to solar energy; a negative number indicates relatively stronger exposure to gas. We use *net* solar energy investments because (a) this mirrors the setup of the IAT, which is also a measure of relative preference of one energy source over the other, (b) it allows us to cancel out the effect of systematically different investment patterns of financial versus strategic investors.

2.1.3. Sample

Our survey targeted professional Swiss energy investment decision-makers. Within each company, we approached the person who is responsible for energy investments. Depending on the type of investor, the person in charge for energy investments is at a different level within the hierarchy; within electric utility companies, the head of portfolio management was the most appropriate person to talk to; within small financial investors (e.g. pension funds), we approached those who define the investment strategy, typically members of the board. Within larger financial investors, more specialized portfolio managers turned out to have the most in-depth insights on energy investment decisions. Altogether, 370 financial investors (investment managers in banks, pension funds, insurance companies, etc.) and 66 strategic investors (investment managers in energy companies) received the invitation to participate in Study 1. Before the IAT section of the questionnaire, participants read a short introduction and detailed instructions for the following reaction test. Of the 114 participants who entered the test between

[2] In the Study 1 version of the IAT, a respondent scoring −2 would have a strong association of gas with return and photovoltaics with risk, whereas a respondent scoring +2 would associate photovoltaics = return and gas = risk.

Table 2
Socio-demographics of the sample of Study 1 ($N = 35$).

Company type (*N*)	
Electric utility company	7
Banks	2
Institutional investors	26
Position within the company (*N*)	
CEO or member of the board	9
Chief financial or investment officer	20
Portfolio Manager	5
Other	1
Demographics (years)	
Age	43.9 years (SD = 9.7)
Experience in investment decision-making	7.6 years (SD = 6.9)
Experience in energy investment decision-making	4.2 years (SD = 5.6)

June and September 2012, 78 participants proceeded to the IAT. Forty-nine respondents completed all 180 reaction tasks. Of the 49 complete tests, 4 had to be deleted because more than 10% of trials were below 300 ms reaction time, indicating that these participants just rushed through the IAT. The remaining sample size consists of 45 IAT-scores. At the end of the survey, a series of stated preference items followed. Of the 45 participants with a usable IAT-score, 8 did not finish the questionnaire. Two participants did not work for a strategic or financial investor and were excluded from further analysis. The cleaned sample used for further analysis consists of 35 participants. Besides the fact that our target population is a set of very busy managers, an additional challenge for the distribution of the test was the fact that participants had to install a plug-in on their computer to run the test. Several potential participants, in particular those working for Swiss banks, could not run the test due to firewall-problems. Therefore, the final sample of Study 1 includes only two managers working for a bank. The majority of participants work for an institutional investor (i.e. insurance companies, independent asset management companies, pension funds). Twenty-nine of 35 participants have a senior position within their company. The average age is 44 years and we have a sample of managers with, on average, eight years experience in investment decision-making and four years energy domain-specific experience (see Table 2).

2.2. Results

2.2.1. Descriptive results

In the final sample of 35 participants, the IAT-score is on average −0.045 (SD = 0.468). We find an almost even split with 16 participants who associate gas more strongly to return and solar energy to risk, 8 participants with equally strong associations of risk and return to gas and solar, and 11 participants with stronger solar = return and gas = risk associations (see Table 3).

In the grid-item following the reaction tasks, we collected detailed information about participants' investments in different energy sources. We distinguished between investments the participant conducts *himself* in his daily business, investments of his or her *company*, and we were also interested in *privately* conducted investments. For further analyses, we used investments a participant undertakes himself in his daily business. We focus on investments in solar energy and gas only, because our IAT also contrasted these two energy sources. Table 4 shows the fraction of the sample investing in solar energy and gas via the respective asset class.

As described in Section 2.1.2, we constructed the dependent variable net solar energy investments by counting, for each participant, the number of asset classes used to invest in solar energy minus the number of asset classes used to invest in gas (see Table 5) and expressing net solar investment as the difference in number of asset classes used to invest in each energy source (see Table 6). We treat the resulting variable as ordinal. Four participants have a value of −1, that is, they use one asset class more to invest in gas than solar energy. Twenty-two respondents have the value 0, that is, they invest in gas and solar energy through the same number of asset classes. Eight managers use one more asset class in solar energy, and one participant uses two more asset classes to invest in solar than gas.

2.2.2. Impact of implicit cognition on energy investments

We find a significant correlation of the IAT-score with behavior ($r = 0.30$). In order to compare this IAT-criterion measure correlation to the mean values found in a review of 122 studies by Greenwald et al. (2009), we apply Fisher's r-to-Z transformation

Table 3
Distribution of IAT-scores in Study 1.

IAT-test result			
Category	Cohen's *d*	Interpretation	Number of respondents per category ($N = 35$)
Strongly pro gas	<−0.65	Stronger association of gas with return,	2
Moderately pro gas	−0.65 . . . −0.35	Stronger association of solar energy	7
Slightly pro gas	−0.35 . . . −0.15	with risk	7
	−0.15 . . . +0.15	Neutral	8
Slightly pro solar	+0.15 . . . +0.35	Stronger association of solar energy	3
Moderately pro solar	+0.35 . . . +0.65	with return, stronger association of gas	4
Strongly pro solar	>+0.65	with risk	4

Table 4
Share of respondents investing in solar energy and gas by asset class (Study1).[a]

	Private equity (%)	Publicly listed equity (%)	Real estate (%)	Bonds (%)	Project finance (%)	Commodities/other real assets (%)	Other (%)
Solar energy	20.0	28.6	8.6	2.9	11.4	5.7	11.4
Gas	8.6	22.9	0.0	8.6	2.9	17.1	8.6

[a] Multiple answers were possible. Numbers do not add to 100% because some respondents do not invest in the respective energy source at all.

Table 5
Number of asset classes used by respondents to invest in solar energy and gas (Study 1).

Number of asset classes	0 (%)	1 (%)	2 (%)	3 (%)	4 (%)	≥4 (%)
Solar energy	31	54	11	0	3	0
Gas	40	49	11	0	0	0

Table 6
Distribution of dependent variable, net solar investments (Study 1).

	Investing in gas through more asset classes than in solar		Equal investment in gas and solar	Investing in solar through more asset classes than in gas		
Difference in number of asset classes (solar–gas)	≤−2	−1	0	1	2	≥3
Number of respondents (*n*)	0	4	22	8	1	0

and find an effect of $r = 0.31$. Greenwald et al. found average $r = 0.27$. Thus, we find a relatively high correlation of the IAT-score with investments.

2.2.3. Discussion

In our final sample of 35 managers we find a positive correlation of implicit cognition with energy investments in the expected direction: The more strongly an investor's association of solar photovoltaics with return and of gas with risk, the higher his investment in solar energy relative to gas. Given the relatively limited sample size of Study 1, our dataset at this point limited our ability to do further analysis. In order to test if the relation of implicit cognition with investments prevails when taking into account control variables such as company type and personal characteristics of a manager, we decided to conduct Study 2.

3. Study 2

3.1. Method

To establish a bigger sample in Study 2, we decided to collaborate with Project Implicit – the spin-off that Greenwald et al. launched at Harvard University when they developed the IAT. Project Implicit hosted the IAT of Study 2 on their webpage. This offered the advantage that participants of the IAT did not need to install a plug-in anymore. Furthermore, for the design of Study 2 we benefited from several additional insights. Study 1 was in English, which was due to the fact that we had participants speaking different languages (mostly German and French). In order to control for confounding effects due to language problems, we surveyed our participants' English skills and did not find a significant correlation of language skills with the IAT-score ($r = -0.14$). Nevertheless, we had received the feedback that some managers did not participate in Study 1 due to language barriers. Thus, the survey language in Study 2 was German, which is the language spoken by two thirds of the Swiss population. In terms of IAT-design, the most notable difference between Study 1 and Study 2 are the terms used to describe the attributes. The attributes in Study 1 were labeled *risk* and *return* to resemble the mindset of an investment decision-maker. For Study 2, we decided to remain closer to the classic version of the IAT with the more generally termed attributes *positive* and *negative*.

Another small distinction between Study 1 and Study 2 is the wording of the target categories: solar energy seemed to be a more common term than photovoltaics and we used the more precise term natural gas instead of gas. We also fine-tuned the stimulus words to match the new attribute categories, and paid close attention to strict symmetry between the terms used in both categories. The experience from Study 1 showed that the stimuli *small-scale* and *large-scale* were for some test participants not clearly associated to photovoltaics and gas, respectively. Therefore, we did not use them in Study 2. However, these are methodological details, which should not affect the main result of the IAT (De Houwer, 2001). While some of the stimulus words are of different length and it takes longer to read and assign *high market potential* than to read and assign *gas*, any effects, if existent, should cancel out across the different constellations (remember that the IAT score is based on differences) (Table 7).

Table 7
Target categories, attributes and stimuli of the IAT (Study 2).

Target categories	Stimuli
Solar energy	Solar cell, renewable, solar energy, solar power plant
Natural gas	Gas, fossil, gas fired power plant, shale gas
Attributes	
Positive	Profit, growing market, high return, high market potential
Negative	Loss, shrinking market, low return, low market potential

3.2. Sample

The target population in Study 2 is identical with that of Study 1, but investors who already participated in Study 1 were excluded from Study 2. Altogether, 488 investors received the invitation to the survey. After the introduction to the survey but before running the IAT, participants were asked to fill in the most relevant information about the company they work for and their position within that company. This was a lesson from Study 1, where eight participants completed the IAT section, but quit the survey before answering demographic questions. Of the 126 investors who entered the test in March and April 2013, 88 proceeded to the IAT. For 86 participants, a *d*-score was calculated by Project Implicit. However, 40 of the 86 participants had to be excluded from the sample because they failed in more than 10% of the reaction tasks. Of the remaining 46 participants, four did not indicate the type of company, leading to a cleaned final sample of 42 participants. In Study 2, the plug-in problem (which, in Study 1, affected bankers the most) no longer persisted and hence the proportion of bank managers is clearly higher than it was for Study 1. Furthermore, seniority is slightly lower in the sample of Study 2. However, mean energy domain-specific experience is the same in both studies with 4.2 years.

3.3. Results

3.3.1. Descriptive results

The IAT-score of the entire sample is 0.639 (SD = 0.543). Overall, we find a moderately stronger association of the attribute *positive* to solar energy than to gas (and thus a stronger association of the attribute *negative* to gas than to solar energy). Table 8 shows the IAT-results of the final sample of 42 respondents in Study 2. More than half the sample has even strongly more positive associations to solar energy and more negative associations to gas (indicated by IAT score >0.65) (Table 9).

To measure explicit associations to solar energy and gas, we asked participants to indicate the extent to which they associate gas with "positive", gas with "negative", solar energy with "positive" and solar energy with "negative" on four 7-point Likert scales ranging from "weak" (1) to "strong" (7). The order of the four items of the grid was randomized, as well as whether the explicit associations were measured before or after the IAT. For further analysis we condensed the information from the four items into one single scale that mirrors the IAT-score: Positive associations to solar energy and negative associations to gas were added, negative associations to solar energy and positive associations to gas subtracted (a similar procedure to condense the explicit items was suggested

Table 8
Descriptive statistics of the sample of Study 2 (N = 42).

Company type (N)	
Electric utility company	9
Banks	18
Institutional investors	15
Position within the company (N)	
CEO or member of the board	6
Chief financial or investment officer	11
Portfolio Manager	12
Analyst	9
Other	4
Demographics (years)	
Age	41.2 years (SD = 8.74)
Experience in investment decision-making[a]	6.3 years (SD = 6.45)
Experience in energy investment decision-making[a]	4.2 years (SD = 4.76)

[a] 1 participant did not answer the experience-items.

by Greenwald et al., 2003). The resulting explicit-association score ranged from −12 (strongest combination of positive associations with gas and negative associations with solar) to +12 (vice versa). The mean value of explicit associations to solar energy versus gas is 3.405 (SD = 3.819), so the explicit items reveal consistently with the IAT-score more positive associations to solar energy.

Energy investments were again surveyed in a detailed grid-item in which participants had to indicate via which asset classes they invest in which energy sources. In order to minimize the cognitive load for respondents, we reduced the number of asset classes from seven (Study 1) to four (Study 2): the three most widely used (project finance, shares, bonds) plus "others". To compute the final ordinal dependent variable, we applied the same procedure as in Study 1. The investment pattern of our participants of Study 2 is similar to those of Study 1: In Study 2, nine participants used one

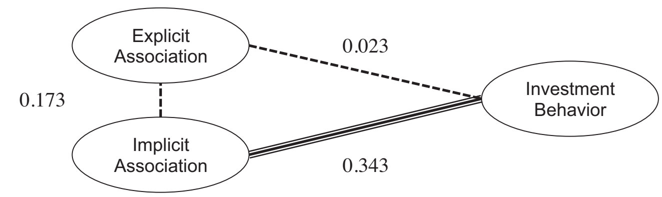

Fig. 2. Correlation of implicit and explicit associations with energy investment behavior.

asset class more to invest in gas than in solar energy, 21 participants used the same amount of asset classes to invest in both energy sources, eight participants used one more asset class for solar and four used two more asset classes for investments in solar energy than in gas.

3.3.2. Comparing the influence of implicit and explicit associations

In Study 2, the correlation of implicit associations with investments is 0.340 – which is similar to the one found in Study 1 (r = 0.310). The correlation of explicit associations with investments is almost zero (r = 0.02). Finally, the correlation of the IAT-score with the explicit score is 0.173, which is not significant either, given our sample of n = 42 (Fig. 2).

This preliminary analysis indicates that the IAT-score has relatively high predictive power for investments when compared to explicit cognition. We test this finding in a hierarchical ordered logit regression.

Table 10 shows in the two columns on the left the results with control variables age, investor type and position of the participant within the company. This baseline model reveals a negative effect of

Table 9
Distribution of IAT-scores in Study 2.

IAT-test result			
Category	Cohen's d	Interpretation	Number of respondents per category (N = 42)
Strongly pro gas	<−0.65	Stronger positive association with gas, stronger negative association with solar energy	1
Moderately pro gas	−0.65 . . . −0.35		3
Slightly pro gas	−0.35 . . . −0.15		1
	−0.15 . . . +0.15	Neutral	1
Slightly pro solar	+0.15 . . . +0.35	Stronger positive association with solar energy, stronger negative association with gas	2
Moderately pro solar	+0.35 . . . +0.65		11
Strongly pro solar	>+0.65		23

Table 10
Ordered logit regression results of Study 2.

Variables	Model 1		Model 2		Model 3	
	Net solar energy investments	Robust standard error	Net solar energy investments	Robust standard error	Net solar energy investments	Robust standard error
IAT-score					0.656*	0.351
Explicit score			0.080	0.335	−0.0977	0.368
Age	−0.844*	0.455	−0.847*	0.447	−0.831*	0.458
Bank[a]	−2.859**	1.417	−2.820**	1.37	−3.070**	1.305
Institutional investor[a]	−0.758	1.197	−0.732	1.171	−1.150	1.079
Chief financial or investment officer[b]	−1.003	1.231	−0.973	1.223	−0.855	1.141
Portfolio manager[b]	−2.120*	1.163	−2.100*	1.157	−2.026*	1.123
Analyst[b]	−2.349*	1.353	−2.343*	1.34	−2.104	1.364
Other position[b]	−2.146	1.465	−2.136	1.434	−1.610	1.378
Pseudo R^2	0.215		0.216		0.247	
Prob > Chi^2	0.008		0.009		0.011	
Observations	42		42		42	

All variables (except dependent variable) are standardized.
[a] Reference group electric utility company.
[b] Reference group CEO or member of the board.
* $p < 0.1$.
** $p < 0.05$.

age: the older an investor, the lower his relative amount of investments in solar energy vs. gas. Working for a bank ceteris paribus implies clearly less net investments in solar energy and we also find a slightly negative effect if a participant was lower in the hierarchy of the company. The next model shows the results if the explicit score is included. The coefficient of the explicit score is not significantly different from zero, which means that what our participants explicitly said about solar energy and gas has no significant impact on their personal investment behavior within the company. The added explanatory power of the explicit score is low, as the pseudo R^2 increases by only 0.001. The final model in the columns on the right includes the IAT-score, too. Again, the strongest effect comes from the control variable investor type. Nevertheless, the IAT-score has a significant impact, too; more positive implicit associations to solar energy imply a higher investment exposure to solar energy. With the IAT-score as explanatory variable, the power of the model increases from 0.216 to 0.247.

3.3.3. Discussion

Just as in Study 1, we find a clear correlation of the IAT-score with investments in Study 2. Furthermore, the larger sample size allowed us to include the most important control variables in a regression model to see if the effect prevails if we assume a causal relation. Whereas investor type clearly has the strongest effect on investments, the ordered logit regression model also confirms a significant effect of the IAT-score on investment. In Study 2 we also tested if the effect prevails if we control for explicit associations and find that it does indeed; implicit cognition correlates more strongly with behavior than explicit cognition. The zero-correlation of explicit cognition with behavior might be surprising; however, in their review of 122 IAT-studies, Greenwald et al. (2009) find similarly low explicit-behavior correlations in particular in race-IATs. A prominent explanation for this result is social desirability, which might lead to biased measurements, for example in the context of explicit race-attitudes. For our study context of professional investment decision-makers, we do not assume that social desirability might lead to biased explicit statements on solar energy and gas. More promising explanations for the dominant role of implicit cognition in our context can be found in organizational studies (e.g. Dane & Pratt, 2007; Garud & Rappa, 1994; Khatri & Ng, 2000; Tripsas & Gavetti, 2000), which show that intuitive decision-making is particularly prominent in contexts of high uncertainty.

4. General discussion

4.1. Summarizing remarks

The most important findings of our two studies are threefold:

(1) When tasked to assign terms representing financial equivalents to the attributes *positive* and *negative* to either gas or solar, investors exhibit closer associations of **solar** to **positive** attributes, and **gas** to **negative** attributes.
(2) The correlation between the **implicit** variable and investor behavior is significant in both studies and in the expected direction – more positive associations to solar energy (in comparison to gas) imply more investments in solar energy (in comparison to gas).
(3) The correlation between the **implicit** variable and investor behavior is *stronger* than the correlation between the **explicit** variable and investor behavior.

While this is, to the best of our knowledge, the first ever application of the IAT with professional investors in the energy domain, our results are consistent with the main findings of the IAT-literature. Just as earlier IATs opened up the black box on racial attitudes for example and showed that racial prejudices influence behavior of lay people as well as judges in their decision-making in criminal cases with black defendants (Rachlinski, Johnson, Wistrick, & Guthrie, 2009), we opened up the black box on attitudes toward renewable and fossil energy sources, and find a significant correlation between implicit cognition and investment behavior. As we can see from Study 2, this relation is stable and prevails if we control for explicit cognition and control variables. Another result from Study 2 that further highlights the added value of an IAT for the understanding of professional investors' decision-making is that implicit cognition is more closely correlated to behavior than explicit cognition. Thus, while the IAT enhances our understanding of energy investment behavior, taking into account what participants explicitly said they would think did not improve explanatory power of our model. However, one should also bear in mind that organizational factors had more predictive power than the IAT-score to explain the energy investments a manager undertakes in his daily business. Put differently, organizational factors have the most predictive power in our final model, followed by implicit cognition and other individual factors such as age, and explicit cognition has least predictive power in our model.

Comparing Study 1 and Study 2, we find that implicit associations are more pronouncedly positive in Study 2 than Study 1, possibly reflecting a shifting overall investment environment that looked more promising for solar and less promising for gas in 2013 (when Study 2 was conducted) than in 2012 (when Study 1 was conducted).

Given the overall more positive associations to solar than gas, it is a remaining puzzle why professional energy investors still account for the minority of new photovoltaics projects. There are at least two possible explanations for this: time and institutional constraints. From a timing perspective, we might simply be observing a delayed reaction of professional investors to the emerging opportunities in solar, where shifting preferences are not (yet) reflected in investment flows. Alternatively, the difference between implicit associations and behavior could be reflecting institutional constraints, which hinder professional investment managers from doing what they implicitly think might be the right thing to do.

4.2. Practical implications

Energy investors are not just cold, analytical information processing machines maximizing risk-return profiles, but they are human beings, and as such they hold unconscious assumptions about certain investment categories, such as renewable or non-renewable energies. Our results suggest a strong correlation between implicit cognition and investor behavior, whereas the correlation between explicit cognition and both investor behavior and implicit cognition is rather weak. Understanding implicit cognition can therefore be an important ingredient when it comes to describing investor choices. For policy makers interested in facilitating the energy transition, simply addressing the explicit, conscious level of decision-making may not be enough to incentivize changes in investor behavior. Implicit associations may hinder investment in new energy technologies in ways that are not obvious to the observer, and sometimes inaccessible to the decision-maker himself. However, there is also good news: the strongly positive implicit associations to solar energy uncovered among investors in Study 2 suggest that an environment that allows investors to follow their intuition might actually lead to "better" (in the sense of: more closely aligned with societal goals of mitigating climate change) investment decisions.

We would caution, however, that while trying to come to a deeper understanding of implicit cognition in the context of energy investment decision-making is a worthwhile endeavor for further research, the literature on dual process theories provides less clear directions as to which conclusions should be drawn in cases where implicit and explicit cognition are not aligned. On one hand, research in the legal domain has shown that confronting trial judges with their implicit prejudices may lead to less biased decision-making (Rachlinski et al., 2009), on the other hand, more cognitive introspection is no guarantee for better outcomes, for example because it suppresses intuitively accessible information from prior experience (Nisbett & Wilson, 1977; Gigerenzer, 2007), or simply because it slows down the decision process (Goldstein & Gigerenzer, 2009). Diagnosing implicit cognition adds an important dimension to prior research and policy practice, but drawing conclusions for "therapy" of investor behavior is no trivial task.

4.3. Limitations and further research

Our study makes a couple of key contributions. There has been only a handful of applications of the IAT to the energy domain so far (Siegrist, Keller, & Cousin, 2006; Truelove, Greenberg, & Powers, 2014), and ours is the first to investigate implicit cognition in the context of professional energy investment decisions. This required an innovative approach to adapt the IAT design to terminology that resonates with decision-makers' cognition, as well as a novel approach to measuring behavior. The quality of respondents – professional Swiss energy investors – in our sample is in our view a particular strength of the research described here. Notwithstanding these unique features, we acknowledge that as an early exploration into unchartered territory, our research is subject to a number of limitations that can mark starting points for further research.

First, while our dependent variable, net solar energy investments, has been developed in response to the challenges of comparing behavior across different investor categories (e.g. electric utilities and pension funds), we are well aware that this ordinal variable is not an exact measure of investor behavior. By counting the number of asset classes through which a respondent invests in solar energy and gas, respectively, we cannot capture possible systematic differences in the amount of capital invested in each asset class. To give an extreme example, an investor holding a large number of shares in a publicly listed gas company, but small stakes in both a publicly listed solar company and a solar project finance bond would score +1 on our scale, leading us to categorize him as investing more in solar than in gas. While we do not have specific evidence that such systematic differences exist, we would encourage further research exploring alternative, and possibly more accurate measures of investor behavior – while keeping in mind the time and privacy constraints that come along with conducting surveys in a professional investor context. For example, the most accurate measure of energy investments would have been the exact amount invested in each energy source in Swiss Francs. However, this would have required substantial research from our respondents themselves, and the time required to complete the survey would have gone well beyond the usually acceptable 15–20 min, which for busy investment professionals in a high-income country implies substantial opportunity cost. Furthermore, investment decision-makers might be reluctant to provide more precise information on the amount they invest in different energy sources due to confidentiality concerns.

A second limitation is the sample size. Taking both studies together and comparing our sample size to the student samples reported in other IAT studies, we believe surveying seventy-seven professional investors is a remarkable achievement, but obviously future research replicating our study with larger sample sizes (possibly in larger countries than Switzerland) would be welcome. A larger sample would also allow a closer look into the moderating influence of investor type.

A third limitation of our study is that we use an individual-level phenomenon (implicit cognition) to explain behavior that occurs in an organizational context (Russell & Friedrich, 2015). We have taken measures to address any challenges arising from this. As described in Section 2.2.1 above, we asked respondents explicitly to answer the questions about their own investment behavior in a professional context, and separately controlled for their private investment decisions and their firm's investment strategy, respectively. But obviously professional investment decisions always occur in an insitutional context, and further research trying to disentangle individual from institutional influences is welcome. If one assumes that there is in fact relevant information engraved in implicit cognition, then such research could help to further think about institutional environments that balance coherent corporate strategies and risk management procedures with room for intuitive decision-making.

Fourth, the results of our regression analysis suggest that implicit cognition is in fact a driver of investor behavior. To fully exclude the possibility of reverse causality, however, future research could employ longitudinal research designs, tracing investment decisions over a longer period of time. Doing this with real decisions of professional investors is certainly a methodologically challenging endeavor, but resorting to less time-constrained retail investors and/or measuring stated preferences over time, for example with an investor panel participating in a series of choice experiments, could be possible ways forward.

Conflict of interest statement

The authors declare that they have no conflict of interest.

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